An Intelligent Wheelchair to Enable Safe Mobility of the Disabled People with Motor and Cognitive Impairments

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Abstract. In this paper, we develop an Intelligent Wheelchair (IW) system to provide safe mobility to the disabled or elderly people with cognitive and motor impairments. Our IW provides two main functions: obstacle avoidance and situation awareness. Firstly, it detects a variety of obstacles by a combination of a camera and 8 range sensors, and finds the viable paths to avoid the collisions of obstacles based on learning-based classification. Secondly, it categorizes the current situation where a user is standing on as sidewalk, roadway and traffic intersection by analyzing the texture properties and shapes of the images, thus prevents the collisions of vehicle at the traffic intersection. The proposed system was tested on various environments then the results show that the proposed system can recognize the outdoor place types with an accuracy of 98.25% and produce the viable paths with an accuracy of 92.00% on outdoors.

Keywords: Intelligent wheelchair · Obstacle avoidance · Situation awareness · learning-based path generation

1 Introduction

With the increase of elderly and disabled people, a wide range of support devices and care equipment have been developed to help improve their quality of life. Traditionally, the wheelchair, including powered and manual ones, is the most popular and important assistive device for the disabled and the elderly. In particular, Intelligent Wheelchairs (IWs) have received considerable attention as mobility aids [1-5]. Essentially, IWs are electric powered wheelchairs (EPWs) with an embedded computer and sensors, giving them intelligence. Two basic techniques have been used to develop IWs: 1) navigation techniques for automatic obstacle avoidance and 2) convenient interfaces that allow handicapped users to control the IW themselves using their limited physical abilities.

In this study, our goal is to develop the navigation techniques that allow the multiply disabled with cognitive and motor impairments for more safe mobility.

During last decades, many navigation systems have been investigated for IWs, and most of them have used a combination of bumpers, infrared (IR) sensors, ultrasonic sensors, and sonar sensors for collision avoidance [2-7]. Such sensor-based navigations

L. Agapito et al. (Eds.): ECCV 2014 Workshops, Part III, LNCS 8927, pp. 702–715, 2015.
DOI: 10.1007/978-3-319-16199-0_49

consider objects protruding more than a certain distance from the ground as obstacles. The NavChair was presented for the elderly people [2], which can detect various obstacles with range sensors such as IRs and ultrasonics, and help the user safely past obstacles and narrow space. The robotic wheelchair was developed by Yanco et al. [3], which provides the avoidance of obstacles and automatic following of a target specified by the user (e.g. follow a person walking in front of the wheelchair). In addition, a drive-safe-system (DSS) was developed to provide safe and independent mobility to the visually impaired [4-5]. The DSS can detect various obstacles using 2 bumpers, 5 IRs and 5 ultrasonics, and provide the wall following and door crossing in indoors. Such sensor-based navigations are simple, inexpensive and easy to install, and are thus widely used. However they suffer from specular reflections and poor angular resolution. In addition to detect various obstacles such as small or flat objects, they require many sensors with high capacity.

As an alternative method to sensor-based navigation, a method has been received a lot of attention [8-12]. The vision-based navigation is further categorized into methods using stereo and monocular vision. The methods using stereovision techniques discriminate obstacles from the backgrounds by 3D depth information. The major drawback of such methods involves high computational time and hardware costs. On the other hand, the monocular vision-based navigations have used the image processing and computer vision technique to recognize the obstacles, where obstacles are considered as objects that differ in appearance from ground. Accordingly, an appearance model to describe the visual properties of background is required, which should be robust to some situational effects such as cluttered background and illuminations. In [13], online background model is proposed that can be easily learned on real-time, which can work well on both textured and texture-less background and improve the sensitivity to illumination.

Although many navigation systems are working well on indoors and outdoors, they still have one major problem. In real outdoor environments, many accidents have occurred on the traffic intersections, which are more dangerous places to the disabled people and cognitively impaired people. To fully guarantee the safety of the wheelchair users, the mechanism to recognize the outdoor situation should be also attached to the IWs.

In this paper, we present a new intelligent wheelchair (IW) to provide safety to the people with various disabilities and the elderly people. To guarantee the safe mobility, the proposed IW supports two main functions: obstacle avoidance and situation awareness. With these functions, it can detect a variety of obstacles and dangerous situations on real environments and recommend safe paths to avoid them. Firstly, the obstacles are recognized by the combination of a camera and 8 range sensors, then viable paths are generated by learning-based algorithms such as a neural network (NN) and a support vector machine (SVM). Secondly, to prevent the collisions with vehicles on the traffic intersection, the situation awareness classifies the place types where a user is standing on as sidewalk, roadway and intersection by texture classification and shape filtering.

To evaluate the effectiveness of the proposed IW, several datasets have been collected from real environments with various illumination types and complex structures, and then the experiments were performed. Then, the results showed that the proposed system can recognize the outdoor place types with an accuracy of 98.25% and produce the viable paths with an accuracy of 92.00% on outdoors.

2 Proposed Intelligent Wheelchair

The goal of this study is to provide safe mobility to a wheelchair user while the users are controlling the wheelchair to their destination. To provide the safe mobility it should detect a variety of obstacles and dangerous situations on real environments and recommend safe paths to avoid them. For this, we present a hybrid obstacle avoidance and a situation awareness.

Figure 1 shows the architecture of the proposed IW, which is composed of an electric powered wheelchair, one camera, 8 ultrasonic sensors, laptop computer and data acquisition (DAQ) board. Through analyzing the images obtained from the CCD camera, we can recognize the upcoming obstacles and the place types where a user is standing on, so prevent the collisions of obstacles with various obstacles including the static walls, pedestrian and vehicles on the traffic intersections.

The proposed IW is composed of four main modules: 1) situation awareness, 2) vision-based obstacle avoidance, 3) sensor-based obstacle avoidance and 4) converter. While a wheelchair user is moving, IW should detect various obstacles and find the viable path to avoid them. For this, a hybrid method is adopted using both sensor values and camera, where obstacles are detected using the sensor values and background subtraction, and viable paths are determined by learning-based classification. In addition, to prevent the collisions of vehicles on the traffic intersections, the situation awareness module discriminated the user's current place as intersection and sidewalk. Finally, all the recognition results are given to the converter that determines most appropriate paths and notifies the decisions to user or directly control the wheelchair.

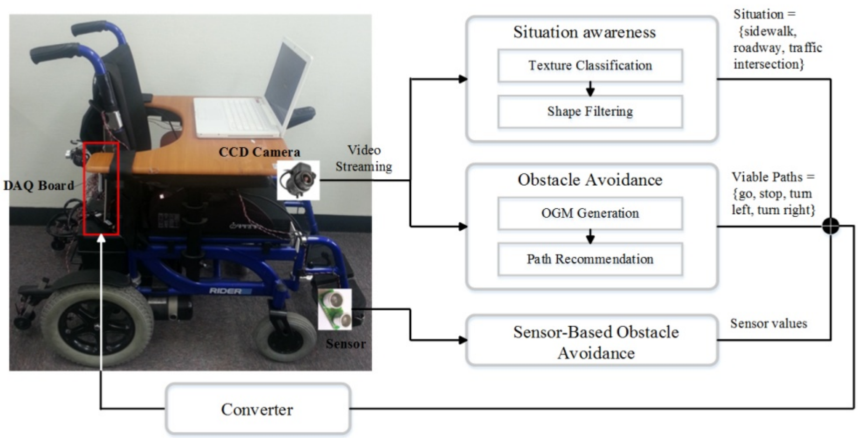


Fig. 1. Overall system architecture

3 Obstacle Avoidance

In our system, to fully guarantee the user's safety, both the camera and the range sensors are used to detect the dangerous situation such as static obstacles and moving obstacles. Then, 8 range sensors can measure only the obstacles within the distance of 2m from the wheelchair, whereas the camera can cover 0.4m to 14m. Thus, the most of the obstacles are recognized by the vision-based algorithm, and sensor-based algorithm is mainly used to recognize the stairs and the obstacles upcoming from the backside of the wheelchair.

3.1 Vision-Based Obstacle Avoidance

Occupancy Map Generation. An occupancy grid map (OGM) represents the environmental information such as the position and size of an obstacle, where each cell models the risk of the corresponding area using gray color levels. In current, we used a camera which has the same focal length of 22mm to human vision and resolution of 320×240 pixels. In this module, the image is transformed to 32×24 OGM, through background color estimation and subtraction.

In this work, the background model is estimated by simple online learning developed by Ulrich and Nourbakhsh [14]. The background color is estimated from only the reference area, that is, 1m-trapezoidal area in front of camera. The input image is filtered by 5×5 Gaussian filters, and transformed into the HSI color space. From the reference area, two color histograms are calculated for Hue and Intensity. These histograms are accumulated for recent five frames, which are used as background model. The background model is continuously updated, as a new frame is input.

Once the background model is obtained, classification is performed. For every frame, each pixel is classified as follows:

$$\begin{cases} M_t = 1 \ \ if \ (|BH_t(s) - H_t(s)|) \le T_H \ \text{ and } (|BI_t(s) - I_t(s)|) < T_I \\ M_t = 0 \ \ otherwise \end{cases} , \quad (1)$$

where the T_H is the threshold value for hue histogram BH_t and T_I is the threshold value for intensity histogram BI_t. In this paper, the hue and intensity thresholds are set to 60 and 80, respectively

Based on the background classification results, the OGM is produced, where each cell is corresponding to one block of 10×10 pixels in the binary image M_t, and its color models the risk of the corresponding area. Here 10 gray-scales are used according to the risk. Then, the gray scale of a cell is determined by 1/10(# of pixels classified as obstacles). The brighter a grid cell, the more closely space obstacles.

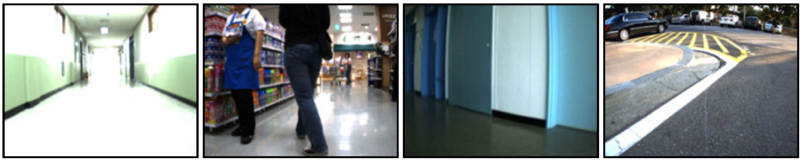
Path Generation. Despite of online learning-based background estimation, the misclassification between background and obstacles can be occurred, as the vision-based system is inevitably affected by time-varying illumination. To compensate the affects by such situational effects, the learning-based path generation is developed.

Here, both a neural network (NN) and a support vector machine (SVM) are considered as the classifier, and the classifier that has the better performance is adapted.

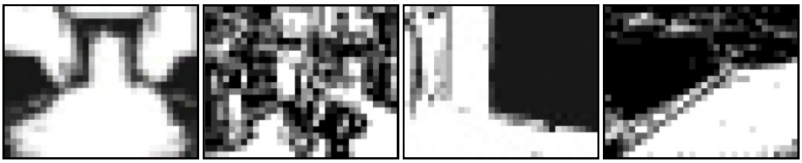
The NN-based classifier is composed of 768 input nodes, 110 hidden nodes and 4 output nodes. It receives the gray values of pixels on 32×24 occupancy map, and outputs four floating numbers that represent the probabilities of four directions to be selected as viable path. Among four directions - Go straight, Stop, Turn Left, and Turn Right, - the direction with the highest value is determined as the viable path.

Unlike the NN that allows for multi-class classification, the standard SVM is has been designed for binary classification problems. To apply such a SVM to four-directions classification, a decision tree is designed, where each node corresponds to one binary classifier that determines if an example belongs to one specific direction class. The decision is performed by three steps: the classification is first performed to divide the current situation into move or stop, the next one is the classification of go and turn, finally the classification of turn-left and turn-right. The SVMs receive the same feature vectors with the NN and use a linear kernel.

The NN-based classifier and SVM-based one were tested with lots of test image collected from real indoors and outdoors, then the result showed the latter is better than the former, which is discussed in experiments.



(a)



(b)

<u>Go(0.9903)</u>	Go(0.0233)	Go(0.5135)	Go(0.7025)
Stop(0.0013)	**<u>Stop(0.9854)</u>**	Stop(0.1654)	Stop(0.0018)
Left(0.0213)	Left(0.0008)	**<u>Left(0.9981)</u>**	Left(0.0005)
Right(0.0945)	Right(0.8912)	Right(0.1004)	**<u>Right(0.9994)</u>**

(c)

Go	**Stop**	**Left**	**Right**

(d)

Fig. 2. Examples of obstacle detection and path recommendation (a) input image, (b) generated OGMs, (c) and (d) recognition results by NN and SVM

Figure 2 shows the result of obstacle avoidance. Figure 2(a) shows the input image and Figure 2(b) shows the generated 32×24 occupancy map result. For the first and fourth images, the proposed method succeeds in correctly detecting the obstacles, while it fails to detect some obstacles in the second image. The main cause is the time-varying illumination. Then, the predicted viable paths by the NN and SVMs are shown in Figs. 2(c) and (d). As you can see, learning-based method can recommend the accurate viable paths.

3.2 Sensor-Based Obstacle Avoidance

Figure 3 shows how the sensors were positioned on the proposed IW. 4 ultrasonic sensors (I1~4) are used for emergency stop if the obstacles are detected in front of IW and find path to avoid them. Also, 4 ultrasonic sensors (I5~8) are used to detect obstacles at back of IW.

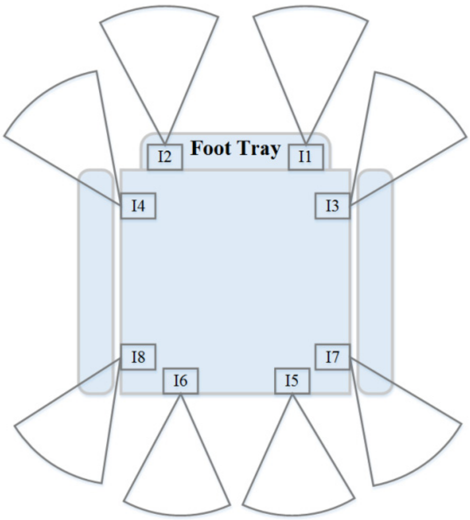


Fig. 3. Position of sensors on proposed IW

By processing the sensors' information, the sensor-based method divides the current paths as 'move' and 'stop,' and it is mainly used to recognize the stairs and the obstacles upcoming from the backside of the wheelchair.

4 Situation Awareness

In addition, through analyzing the images obtained from the CCD camera, we can recognize if the user is approaching to the traffic intersection, thereby preventing the collisions of traffic vehicles.

In this work, a situation means the type of place the user is located, which is categorized into sidewalk and intersection. For recognizing outdoor situation, texture classification and shape filtering were performed on the input image.

4.1 Texture Classification

We first apply Gaussian filter and histogram equalization to the input image in turn. Then, the input image sized at 640×480 is divided into 768 sub-regions sized at 20×20 and texture classification is performed on the respective sub-regions.

To discriminate the boundaries between sidewalks and roadways from other lines, the texture properties of sub-regions are investigated.

In this work, to characterize the variability in a texture pattern, both HOG (Histogram of Oriented Gradient) and color information are used.

The HOG is the feature descriptor to count the occurrences of gradient orientation in the sub-regions of an image, which is many used for object detection [14]. For 20×20 sized sub-region, R the HOG is calculated, which is identified as

$$\mathrm{HOG_R} = \left\{ \mathrm{HOG_R(i)} = \frac{1}{\mathrm{Area(R)}} \times \sum_{\mathrm{j \in R}} \mathrm{magnitude(j)}, \text{if orientation(j)} = \mathrm{i}\ (1 \leq \mathrm{i} \leq 6) \right\} \quad (2)$$

In addition, the average value of pixels' saturation within a sub-region is used to describe the color information, as the pixels corresponding to the roadway have the distinctive saturation distribution.

Based on these textural properties, a rule-based classification is performed on every sub-region. A sub-region is classified as the boundary class if both of the following conditions are satisfied: 1) HOG_R has the larger variance than a predefined threshold θ_H; 2) the average saturation in R, S_R is smaller than a threshold θ_S.

4.2 Shape Filtering

In this step, we determine the outdoor situation based on the orientations of the boundaries: if they are horizontally aligned, the intersection is assigned to the image; if they are aligned close to the vertical, the current image is labeled as side-walk.

To eliminate the affects by misclassified sub-regions and determine correct situation, the profile analysis is performed on the classified images.

Accordingly, a classified image is projected along a y-axis and x-axis and two histograms are computed: horizontal histogram and vertical one. Thereafter, the following three heuristics are applied in turn, to determine the current situation : (1) An intersection is assigned to the current image in which some horizontal his-togram values are more than a threshold; (2) An intersection is assigned to the input image in which the vertical histogram is uniformly distributed; (3) A sidewalk is assigned in which the vertical histogram has the larger variance than a threshold σ. Hence, 10 was set to σ by experiments.

Figure 4 shows the situation awareness. Figure 4 (a) shows the input image. Then texture classification result as shows in Figure 4 (b). As can be seen in Figure 4 (b), the classification results include most of the sub-regions with correct boundary class. And Figure 4 (c) and (d) illustrate how the situation is determined. Figure 4 (c) is a y-axis projection profile of a classified image, and Figure 4 (d) is an x-axis projection profile of a classified image. As you can see in Figure 4 (c), the top image has the vertical histogram with larger variance, thus its situation is considered as sidewalk. On the other hand, the bottom image has some horizontal histogram values larger than a threshold, thus its situation is determined as intersection.

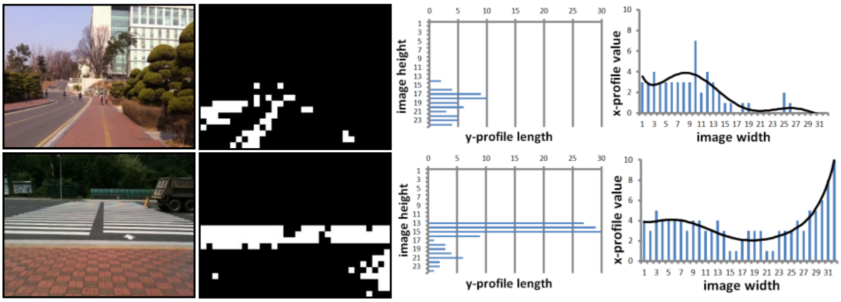


Fig. 4. Shape filtering results (a) Input images (b) texture classification results (c) horizontal projection profiles (d) vertical projection profiles

5 Converter

The Converter receives all of the recognized results in situation awareness and vision-based and sensor-based methods, and determines more appropriate decisions to support users' safe mobility. Table 1 illustrates the decision function to select the viable paths among the results given from three modules.

Table 1. The decision function to select the viable paths in Converter

Input: real time image streaming *I*, 8 sensors values *S*
Output: values paths *v* = {go, stop, turn-left, turn-right}

Selecting the viable paths on converter(*I*, *S*)
{
  a = Situation awareness(*I*);
  b = Sensor-based obstacle avoidance (*S*);
  c = Vision-based obstacle avoidance (*I*);

  if (*a*== 'intersection') *v* ←'stop'
  else if (*b*=='stop') *v* ←'stop'
  else *v* ←c;

  Interface(*v*);
}

Such a decision is conveyed to the user through auditory interface or visual interface. Figure 5 shows the visual interface, where the recognized results are displayed onto the Notebook screen (see the right image of Figure 5).

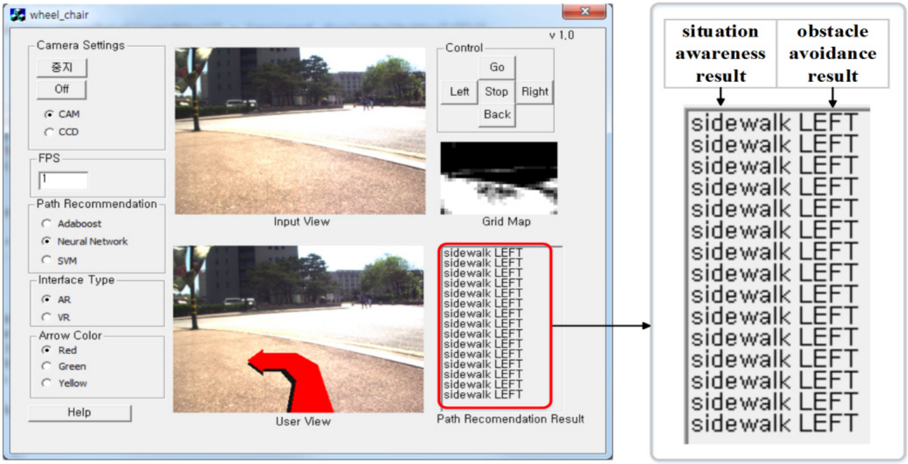


Fig. 5. Visual user interface

Some of the cognitively impaired or the elderly people has the difficulties in controlling the wheelchair in real-time, so the collisions with the dangerous obstacles can be occurred. To prevent them, the Converter allows the direct control of the wheelchair according to the recognized results from three modules.

As shown in Figure 1, our IW uses a DAQ board to translate the recognition results into control commands for the IW. Similar to a general electric powered wheelchair, which is controlled by the voltage passed to the joystick, a DAQ board (USB-6009) is used to transform the ADC function and DAC. The board is connected to a computer through a serial port and programmed using Visual Studio. The board program then controls the directions of wheelchair by modifying the voltage passing through the wheelchair.

6 Experimental Results

To assess the effectiveness of the proposed IW, experiments were performed on the images obtained from indoors and outdoors. For the practical use as mobility aids, it should be robust to environmental factors, such as different place types and lightening conditions. Therefore, 80,000 indoor and outdoor images, including official buildings, department stores, and underground areas, were collected over one year at different times. For all images, the ground-truth was manually labeled by human. Among them, some images were used for evaluating the proposed outdoor situation awareness and some were used for evaluating the performance of the obstacle detection.

6.1 Obstacle Avoidance Results

In this section, we investigated the performance of obstacle detection with a huge data. Unlike the outdoor situation awareness, this module was evaluated using images obtained from both indoors and outdoors.

Table 2 shows the dataset used for evaluating the obstacle detection module. A total of 80,000 images were collected, which were then categorized into 4 datasets, according to their illumination, background texture, and obstacles.

Table 2. The experimental data for evaluating the obstacle avoidance

Places	DB Sets	Illumination	Background texture	Obstacles
Indoor	DB I CCD daytime	- Fixed illumination (fluorescence)	- Little reflection - Weakly textured floor	- Only static obstacles
	DB II CCD daytime	- Fixed illumination with pin light	- High reflection - Marble textured or highly textured floors	- Static and dynamic obstacles
Outdoor	DB III CCD daytime	- Direct sunlight with little shadow	- Weakly textured ground with small road signs	- Static Obstacles
	DB IV CCD daytime	- Direct sunlight with complex shadow	- Reflection by sunlight - Highly textured ground	- Static and dynamic obstacles (moving people and vehicles)

To assess the validity of the proposed method, the results were compared with those of existing method using vector field histogram (VFH) [15].

Figure 6 shows results tested on various environments. Figure 6(a) to (d) show the generated OGMs and determined viable paths. As you can see, the proposed method can accurately predict the viable paths to prevent the collisions of obstacles.

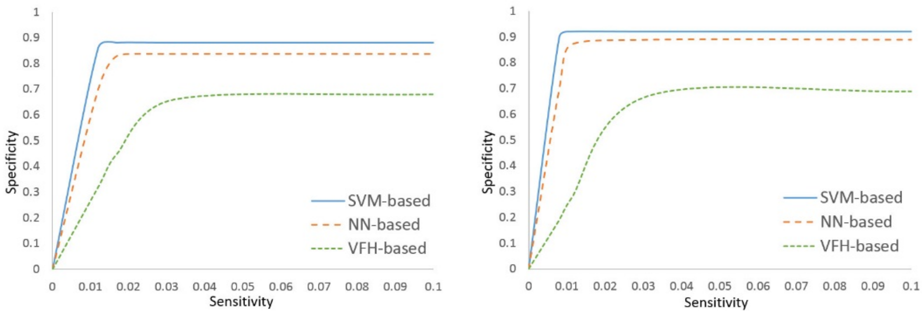
(a) (b) (c) (d)

Fig. 6. Obstacle avoidance results (a) – (d): the input images and OGMs determined as go-straight, stop, turn-left and turn-right

Figure 7 shows the performance summarization of obstacle detection under indoors and outdoors, for three methods – VFH-based method, NN-based method and

SVM-based method. On average, VFH-based method has accuracy of 68.00% and 68.80% on indoors and outdoors, respectively. On the other hand, the SVM-based method can generate avoidable paths in the accuracy of 88.00% and 92.00% on the respective environments, and NN-based method has accuracy of 83.80% and 89.00%.

As you can see, the learning based method showed the better performance; in particular, it can significantly improve the performance on the outdoors– improvement of 20.20%, at least. And the SVM-based classifier showed the superior accuracy to the NN-based classifier.



(a) (b)

Fig. 7. Performance summarization of obstacle avoidance when using three methods (a) the accuracy on indoors (b) the accuracy on outdoors

6.2 Situation Awareness Results

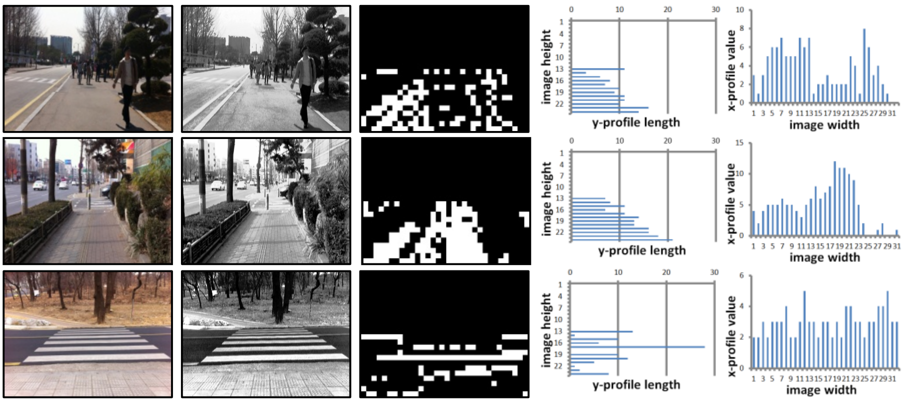
A total of 2243 images were collected, which were then categorized into 6 datasets, according to their environmental complexity, as illustrated in Table 3.

Table 3. The experimental data for evaluating the situation awareness

Environmental Factors		The Number of Images		Usage
Illumination Type	**Scene Complexity**			
Direct sunlight with little shadow	Highly textured ground with static obstacles	110	DB1	Training data
	Textured ground with moving obstacles (people, car)	64	DB2	
	Highly textured ground with static structures	844	DB3	Test data
	Textured ground with simple structures	256	DB4	
Direct sunlight with complex shadow	Non-textured ground with simple structures	156	DB5	
	Textured ground with simple structures	312	DB6	

Among them, 174 images were used as training data for finding optimal parameter set (θ_H, θ_S, σ), which were used for texture classification and shape filtering. And the other images were used for testing.

Figure 8 shows some recognition results for various environments. Figure 8 (a) shows the input images, where the images have the time-varying illumination, and the sidewalks have diverse patterns and colors. The input images were first enhanced through pre-processing stage, which are shown in Figure 8 (b). Then, the texture classification and shape filtering were performed. As shown in Figure 8 (c), the boundaries between side-walks and roadways were correctly extracted, despite of diverse pattern of sidewalks, however they still included some false alarms. To eliminate the affects by misclassified sub-regions and determine correct situation, the profile analysis were performed on the classified images, which are shown in Figure 8 (d). The results showed that the proposed method have a robust performance to the pattern of ground and illumination type.



(a) (b) (c) (d) (e)

Fig. 8. Situation awareness results (a) input image (b) enhanced image by preprocessing (c) texture classification results (d)-(e) horizontal and vertical histograms used in shape filtering

Table 4 summarizes the performance of the situation recognition under various outdoor environments. The average accuracy was about 87.60%. For the DB1 to DB4, the proposed method showed the accuracy of above 96.00%.

Table 4. Accuracy of outdoor situation awareness (%)

	DB1	DB2	DB3	DB4	DB5	DB6	Total
Accuracy	91	95.3	100	100	94.8	97.4	96.42

6.3 Processing Time

The main purpose of the proposed system is to help the safe mobility of the user and to prevent some dangerous collisions with vehicles or obstacles. For its practical use as an assistive device, the real time processing should be supported.

Table 5 shows the average frame processing time in the respective module of wheelchair. In current system, the sensor based obstacle avoidance does not play a role in the overall time metric, as it has own processing power on sensor board. Thus, only the times taken to process the video stream were considered. The processing times were about 228.54ms for the outdoor situation awareness and were about 5.03ms for obstacle detection. As such, the proposed method can process more than 4 frames per second on low-performance computer.

Table 5. Average frame processing time (ms)

Modules		Processing Time
Outdoor situation awareness	Preprocessing	41.24
	Texture classification	181.32
	Shape filtering	5.98
Obstacle detection	OGM generation	2.95
	Path recommendation	2.08
Total		233.57

Consequently, the experiments proved that the proposed method produced the superior accuracy for situation awareness and safe path prediction, thereby assisting safe navigation for the people with various disabilities and the elderly people in real-time.

7 Conclusions

In this paper, an intelligent wheelchair equipped situation awareness was presented to help the safe mobility of the people with various disabilities and the elderly people. The proposed system provides obstacle detection and avoidance, and situation awareness. With them, the proposed IW can detect a variety of obstacles and generate the viable paths to avoid the collisions of them. Moreover, it can recognize the outdoor situations as sidewalk, roadway and traffic intersection, thereby preventing the accidents on the traffic intersection.

To assess the effectiveness of the proposed IW, experiments were performed on the images obtained from indoors and outdoors. For the practical use as mobility aids of the elderly and disabled people, the proposed system should be robust to environmental factors, such as different place types and lightening conditions. Therefore, 80,000 indoor and outdoor images, including official buildings, department stores, and underground areas, were collected over one year at different times. Then the results showed that the proposed method can recognize the situation awareness with an accuracy of 98.25% and produce the viable paths with an accuracy of 90.00%.

Acknowledgment. This research was supported by the MSIP(Ministry of Science, ICT and Future Planning), Korea, under the ITRC(Information Technology Research Center) support program (NIPA-2014-H0301-14-1001) supervised by the NIPA(National IT Industry Promotion Agency) and Basic Science Research Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Education, Science and Technology(NRF-2013R1A1A3013445).

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